A c L O n e t: A Method to Facilitate Automatic Learning-Object Assembly
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Introduction

A c L O n e t = “Assembly from a Collaborative Learning-Object NETwork”

- It automatically assembles Learning Objects (LOs) into lessons, in the domain of elementary geometry.
- For the purpose of this poster, an LO is any digital resource (e.g., text, web page, or picture) that can be used to build a lesson (see Figure 1).
- Our approach considers the following questions:
  - What metadata are needed to make semantic assembly possible?
  - How would an instructor assemble a group of LOs based on these metadata?

Representing LOs

- Metadata = “data that describe other data”
- A c L O n e t uses an LO representation based on established standards, specifically IEEE’s LOM (Learning Object Metadata).
- We found the following metadata particularly useful when attempting automatic assembly:
  - LOM: location, typical learning time, typical age range, learning resource type (e.g., exercise)
  - Other: learning objective, topic, subtopic, pre/post knowledge
  - Ratings: organisation, ease of use, accuracy

Assembly Process

- After the user selects the age level, topic, subtopic(s), duration, and learning objective(s) for a module (see Figure 2), A c L O n e t pre-filters the LOs into a candidate set.
- This set is then sorted based on topic and subtopic, using an ontology, and based on learning resource types (LRTs). E.g., Lesson LRTs appear in the following order: narrative text, examples, exercises, and exam.
- An LO is chosen, with a probability proportional to its overall rating, if more than one LO is available to satisfy any lesson’s LRT slot (e.g., two exam LOs).

Results and Future Work

- The current A c L O n e t prototype can assemble four module types, based on topic and duration: perimeter, area, surface area, and volume.
- The final application will make fuller use of prepost knowledge and user-rating information.
- The following results are expected:
  - A c L O n e t’s solution will yield a semantically meaningful assembly (our test set already contains over 100 geometry LOs); and
  - The methods used to automatically assemble geometry LOs can be applied to other learning domains, with limited changes.